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Mind the price gap: How optimal emission pricing relates to the EU CO2 reduction targets

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Abstract

From the transport economic literature it is known that optimal pricing of (environmental) externalities improves the urban system. In contrast to theory-based optimal pricing strategies, real-world policy setting often follows so-called 'backcasting' approaches where certain targets are set, and policy measures are implemented in order to reach those targets. An example for the latter approach is the EU goal to reduce global greenhouse gas emissions in the transport sector by 20% until 2020 with respect to 1990 levels. This paper aims to (i) compare optimal pricing and backcasting approaches for a specific case study in a simulation environment by identifying the contribution of each approach in EU's 2020 emission reduction target, and (ii) to determine the costs required to reach the desired targets. For this purpose, an optimal emission pricing strategy is applied to a real-world scenario of the Munich metropolitan area in Germany. The highly differentiated tolls relate to individual exhaust emissions, i.e. they are calculated using damage cost estimates from the literature and vary over time of day, with traffic situation, and with vehicle type. The results indicate that the desired reduction in CO_2 emissions is not reached for optimal pricing approach, and that the initial damage costs estimates need to be multiplied by a factor of 5 in order to reach the target, yielding a price of 350 EUR/ton CO_2. When aiming at a decrease of the overall emission costs by 20% (CO_2 *and* local pollutants), the initial cost estimates need to be multiplied by a factor of 10. Furthermore, it is shown that the major contribution to the overall emission reduction stems from behavioral changes of commuters and reverse commuters rather than from urban travelers; under some circumstances, urban travelers even increase their CO_2 emission levels. Hence, the study rises awareness that conflicting trends for different types of pollutants and different types of individuals are very likely: an increase in NMHC levels for urban travelers and freight depicts that pricing emissions does not necessarily result in a reduction of all pollutants or of the emissions levels of all travelers. It is shown how agent-based simulations can be used to provide valuable insights and decision support in such possibly counter-intuitive situations.

Keywords: Sustainable transport, Emissions, Air pollution, Optimal pricing, Backcasting, Agent-based modeling

1 Introduction

Growing motorization and urban sprawl have led to significant increases in transport-related negative effects (emissions, congestion, accidents, noise etc.). For instance, passenger and freight transport in Europe have grown substantially between 1990 and 2010, and the corresponding CO_2 emissions have increased by about 20% (Schoemaker et al., 2012; Eurostat, 2016). Knowing the possible negative impacts of climate change, the European Union (EU) and the international community have agreed on the need to reduce global greenhouse gas (GHG) emissions in order to limit global warming below 2° Celsius (European Commission, 2011; FCCC/CP/2015/L.9/Rev.1, 2016). To achieve this goal, the directive 2008/101/EC (2008) sets the goal to reduce global GHG emissions in the transport sector by at least 20% until 2020 with respect to 1990 levels. In the light of the above, the EU has launched several regulation schemes (European Union, 2017): (a) emission trading system (ETS) (b) use of renewable energy sources (c) reduction in the energy use of buildings and industries and (d) improvement in fuel and vehicle technology.

Looking at the historic trends for the EU-28[1] , the reduction in GHG emissions from all sectors has already reached the 20% reduction goal; however, an increase

[1] See http://europa.eu/about-eu/countries/member-countries/ for a complete list of all EU member countries.

of up to 15% is observed for GHG emissions from road transport (Eurostat, 2016). Future forecasts indicate that passenger and freight transport might grow more than 80% by 2030 with respect to 1990 levels (Schoemaker et al., 2012).

For the transport sector, EU regulations mainly concentrate on improvements in fuel and vehicle technology in order to balance the increase in demand (European Union, 2017; Romm, 2006). As a consequence, the average CO_2 emissions from new cars registered in 2014 are as low as 123.4 $g\ CO_2/km$, below the 2015 target of 130 $g\ CO_2/km$ (EEA, 2015). However, these numbers are questionable as the growing gap between "type-approved" (emissions tests under laboratory conditions) and on-road CO_2 emissions from the vehicles indicates (Mock et al., 2014; EEA, 2014). That is, improvements in vehicle and fuel technology might not be effective under on-road conditions, which reduces the chance to reach the GHG emissions targets. Even if actually materializing, improvements in fuel and vehicle efficiency implicitly lead to a reduction in the generalized costs of travel. This, in turn, can counteract the positive impact of the technology improvements through rebound (or takeback) effects[2] (see, e.g., Divjak, 2009; Parry and Small, 2005; Barla et al., 2009). For similar reasons, other frameworks assessing low-carbon transport policies account for rebound effects imposed by improvements in vehicle technology and fuel efficiency (Ewing et al., 2007; Nakamura and Hayashi, 2013).

For these reasons, many researchers have criticized the technology-oriented policy setting of the EU and pointed out the important role of regulatory demand- and supply-side policies in order to reach the CO_2 reduction goals (see, e.g., Emberger, 2015; Banister and Hickman, 2009; EEA, 2008; Parry et al., 2014). In contrast to relatively 'hard' traffic restraint policies in the central areas of cities (see Elmberg, 1972; Buehler and Pucher, 2011; Fernandes et al., 2014; Zhou et al., 2010; Cai and Xie, 2011, for real-world examples), pricing schemes offer a less restrictive and more dynamic opportunity of managing transport-related problems in cities. From a theoretical point of view, optimal pricing is a very effective measure to move towards a more efficient utilization of capacities and resources (Verhoef, 2001). Also, it would allow the technological improvements to unfold their full potential (May, 2013). However, only few pricing schemes have been implemented in the real-world, e.g. in Singapore, London, Stockholm (Eliasson et al., 2009), Gothenburg (Börjesson and Kristoffersson, 2015) and Milan (Rotaris et al., 2010).

In real-world politics, the use of so-called 'backcasting' approaches (Geurs and

[2] The rebound effects are mainly categorized in direct and indirect rebound effects (IPCC, 2014; Thomas and Azevedo, 2013). The former relates to the increase in demand because of a decrease in travel costs due to an efficient vehicle; e.g., a fuel-efficient car will have lower operating costs which may increase the vehicle kilometer traveled The latter is the effects from re-spending the savings due to increased efficiency on other goods or services; e.g., spending fuel savings on vacation. The combined effect is called economy-wide rebound effects.

van Wee, 2000, 2004; IWW et al., 1998) is more common than implementing pricing strategies. The idea behind this concept is to set political goals, and implement a number of policy measures in order to reach these goals. For instance, it is used to achieve the 2025 CO_2 reduction targets for the UK (Hickman et al., 2009). With the current trends, chances to achieve these targets were slim and therefore, several policy pathways were identified to help reduce transport-related CO_2 emissions. Overall, there is some indication that there exists a price gap between the actual costs of reducing the CO_2 emission in the transport sector and the existing estimates on the social cost of carbon[3]: Liu and Santos (2015) find that even the highest estimates of the social cost of carbon from the literature is not able to justify the mass introduction of low/zero emission vehicles/fuel technologies. They can only be justified if the social cost of carbon is revised upwards.

The present study picks up on this observation and aims to compare the price levels obtained from an optimal pricing strategy to those resulting from the backcasting approach. In literature, the former typically aims to quantify damage costs (= social costs), whereas the latter only implicitly defines avoidance (= mitigation/abatement) costs, depending on the chosen pathway (see, e.g., Watkiss et al., 2005; Link et al., 2014; Maibach et al., 2008, for a detailed discussion on damage and avoidance cost). For simplicity, the focus of the study is limited to optimal pricing and backcasting; therefore, only these terms are used throughout this study. In the light of the above, the questions arise

(i) how these two approaches relate to each other, i.e. to what extent optimal pricing of air pollution externalities contributes to the EU 2020 CO_2 reduction target, and

(ii) how (additional) prices would need to be set in order to reach this target. In other words, how the pricing strategy meeting the target would need to be defined.

Thus, in a first step, the present study applies an existing optimal pricing scheme for exhaust emissions to a real-world scenario of the Munich metropolitan area in Germany similar to work by Kickhöfer and Nagel (2016); Agarwal and Kickhöfer (2016); Kaddoura et al. (2017). In a second step, the paper attempts to identify the necessary additional prices, as multiples of the original damage cost estimates, in order to reach the EU 2020 CO_2 reduction targets. The remainder of the paper is organized as follows: Section 2 illustrates the methodology and research approach in more detail. The scenario set up for a real-world case study is exhibited in Section 3,

[3] The social cost of carbon (or marginal damage cost of carbon emission) is defined as the net present value of the impact of one additional Ton (ton) of carbon over the next 100 years which is emitted to the atmosphere today (Watkiss et al., 2005; Downing et al., 2005).

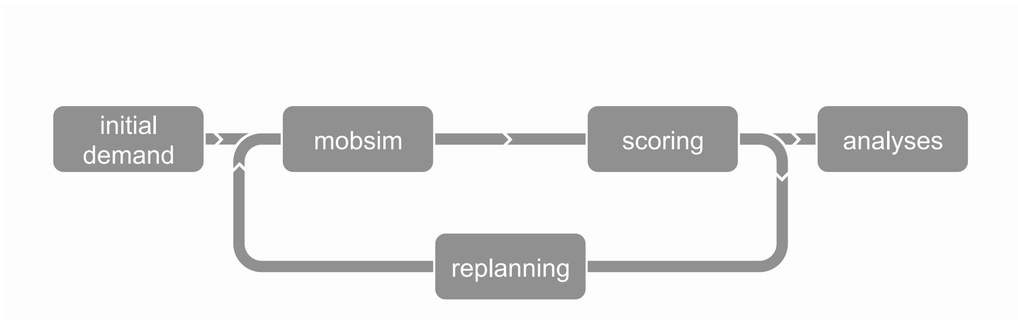
and the results are analyzed in Section 4. Limitations of the presented approach, their potential influence on the results, sensitivities and policy implications are discussed in Section 5. Finally, Section 6 concludes the study and identifies possible directions for future research.

2 Methodology

2.1 Simulation platform – MATSim

MATSim (Horni et al., 2016b) is an modular open-source transport simulation framework designed to simulate large-scale scenarios. It is therefore chosen for all simulation runs. Physical boundary conditions (network data), initial demand (daily plans of all individual travelers (or agents), see Figure 1) and various configuration parameters are minimal inputs.

Figure 1: MATSim cycle (Horni et al., 2016a)



In an iterative co-evolutionary process, every agent in the simulation learns and adapts to the system. This process is composed of the following three steps:

1. **Mobility simulation**: Daily plans of all individuals are executed simultaneously on the network. The network loading algorithm in the MATSim is so called queue model (Horni et al., 2016c), which can simulate large-scale scenarios in reasonable computation time.[4]

2. **Plans evaluation**: In order to model the choice between multiple potential daily plans (choice set), the executed plans of all agents are evaluated using a utility function, indicating the performance (or score) of the plan. Typically, a daily plan of an agent consists of several trips between activities (e.g. home,

[4] In this study, the traditional *"first-in-first-out"* traffic dynamics of the queue model is used (see Agarwal et al., 2015, 2017, for more details and the resulting fundamental diagrams).

work, shopping, home).[5] A plan's utility (S_{plan}) is represented by:

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \tag{1}$$

where N is the number of activities, $S_{act,q}$ is the utility from performing activity q and $S_{trav,mode(q)}$ is the (typically negative) utility for traveling to activity q. Generally, the first and the last activity are stitched together (e.g. home activity) and therefore also scored together; consequently, the activity index runs from 0 to $N-1$. In short, the utility earned from performing an activity is defined by the following function with decreasing marginal utility of activity duration[6]:

$$S_{act,q} = \beta_{dur} \cdot\ t_{typ,q} \cdot \ln(t_{dur,q}/t_{0,q}) \tag{2}$$

where $t_{dur,q}$ and $t_{typ,q}$ are actual and typical durations of activity q, respectively. β_{dur} is the marginal utility of activity duration at $t_{typ,q} = t_{dur,q}$. $t_{0,q}$ is the minimal duration, which essentially has no effect as long as dropping activities is not allowed.[7] The simplified mode-specific utility from traveling by car or public transport (PT) following Nagel et al. (2016) is described by:

$$\begin{aligned} S_{trav,car} &= \qquad\qquad \beta_{trav,car} \cdot t_{trav,q} + \beta_m \cdot \gamma_{d,car} \cdot d_{trav,q} \\ S_{trav,PT} &= C_{PT} + \beta_{trav,PT} \cdot t_{trav,q} + \beta_m \cdot \gamma_{d,PT} \cdot d_{trav,q} \end{aligned} \tag{3}$$

where $t_{trav,q}$ and $d_{trav,q}$ is the travel time and distance between activity q and $q+1$. C_{PT} is the alternative specific constant (ASC) of public transport (PT). $\beta_{trav,car}$, $\beta_{trav,PT}$ are marginal utilities of traveling by car and PT modes respectively. β_m is marginal utility of money which translates money to utility. $\gamma_{d,car}$, $\gamma_{d,PT}$ are monetary distance rates by car and PT modes respectively (Table 3 shows the values of these parameters used in present study).

3. **Plans re-planning**: After executing and scoring plans, a new plan is generated for a predefined share of agents. The new plan is generated by modifying

[5] A daily plan may in principle also contain the home activity only with no corresponding trip. In the present study, such plans are not considered as agents activity patterns are fixed, i.e. induced trips to new or different locations is not modeled.

[6] See Nagel et al. (2016) for a more detailed description on the functional form.

[7] $t_{0,q}$ is given by

$$t_{typ,q} \cdot \exp(\frac{-10}{\frac{t_{typ,q}}{1h} \cdot p})$$

This is designed in a way that all activities at their typical durations ($t_{typ,q}$) will have same utility of performing i.e.

$$S_{act,q}\Big|_{t_{dur,q}=t_{typ,q}} = \beta_{dur} \cdot 10h$$

an existing plan according to predefined choice dimensions (see Figure 3). The new plan is then executed in the next iteration. Agents who do not get a new plan select a plan from the choice set based on a probability distribution which converges to a multinomial logit (MNL) model (Nagel and Flötteröd, 2012).

2.2 Toll calculation and internalization

For the calculation of time-dependent, link- and vehicle-specific exhaust emissions, the paper uses a tool developed by Hülsmann et al. (2011) and further improved and extended by Kickhöfer et al. (2013). It models warm and cold-start emissions; the latter are generated during the warm-up phase of vehicles, whereas the former are generated while driving. The most relevant parameters for their calculation are the time since the engine has been switched off (duration for which the vehicle was parked: in 1 h time bins up to 12 h and assumed as fully cooled down for parking durations longer than 12 h), distance traveled, vehicle characteristics, engine type, road category and the speed of the vehicle. They are derived from the simulation. With these, the HBEFA[8] database provides the resulting exhaust emission values differentiated by type of pollutant.

In order to convert these emissions into vehicle-specific toll values, a marginal social cost (MSC)[9] pricing approach, developed by Kickhöfer and Nagel (2016) is used. It converts the time-dependent, vehicle-specific emissions into a toll by using emission costs factors from the literature (see Table 1).[10] Thus, in the simulation, every time an agent leaves a link, the vehicle-specific, time-dependent toll (for global and local emissions) is calculated and included as monetary payment into the agent's utility function as Δm_q in Equation 4. As a reaction to the toll, agents learn and adapt their behavior within the iterative learning cycle (see Section 2.1). Consequently, agents' decisions are based on MSC, and the external effect is internalized.

$$S_{car} = \beta_{trav,car} \cdot t_{trav,q} + \beta_m \cdot (\gamma_{d,car} \cdot d_{trav,q} + \Delta m_q) \tag{4}$$

The internalization of externalities through optimal pricing can, e.g. in agent-based transport simulations, be used to identify the upper bound of possible efficiency gains in a transport system (see, e.g., Kickhöfer and Nagel, 2016; Kaddoura et al., 2015; Agarwal and Kickhöfer, 2016). However, the calculation of dynamic,

[8] 'Handbook Emission Factors for Road Transport', Version 3.1, see www.hbefa.net

[9] The marginal social costs are the sum of marginal private costs (MPC) and marginal external costs (MEC) (see, e.g., Walters, 1961; Turvey, 1963). In absence of any pricing, the MATSim utility functions includes only marginal private costs i.e. time and money spent for traveling between planned activities (see Equation 1).

[10] Please note that the toll values for exhaust emissions include local pollutants (NMHC, NO_x, $PM_{2.5}$, SO_2) as well as global pollutants (CO_2). For the evaluation of the EU 2020 emission reduction target, only changes in CO_2 emissions are considered.

Table 1: Emission cost factors. Source: Maibach et al. (2008).

Emission type	Cost factor (EUR/ton)
CO_2	70
NMHC	1,700
NO_x	9,600
$PM_{2.5}$	384,500
SO_2	11,000

vehicle-specific emissions is very complex and time consuming, and especially for environmental externalities, it remains unclear whether the cost factors (see, e.g. Table 1) can be determined in a way that they actually represent damage costs. The idea of the present study therefore is to identify the potential price gap between the toll levels obtained from an optimal pricing strategy and the backcasting approach to achieve the EU emissions reduction target. For that purpose, the emission cost factors from Table 1 are increased by a multiplication factor following a parametric approach. In the remainder of this paper, this factor is referred to as "emission cost multiplication factor (ECMF)". The increased emission costs are then charged to the agents who eventually consider them in their decision making (see Equation 4).

2.3 Problem simplification

Due to the complex nature of the research problem, the following simplifications are made:

a) GHG emissions in the EU from the transport sector (excluding international aviation) are dominated by road transport (Eurostat, 2016). Therefore, it is assumed that a 20% reduction in GHG emissions is required from road transport in the Munich metropolitan area (MMA) in Germany as well.

b) In the context of global warming and road transport, the objective of reduction in the GHG emissions is translated to a reduction of CO_2 emissions since it is a major component among the gases released during the combustion of fossil fuels.

c) The travel demand data is available for the survey year (12/2001 to 12/2002) and therefore, the proposed approach is applied to this demand (Follmer et al., 2004).

With the above simplifications, the research problem is reduced to the estimation of the costs required in order to reduce road transport related CO_2 emissions by 20% for MMA with respect to the survey year.

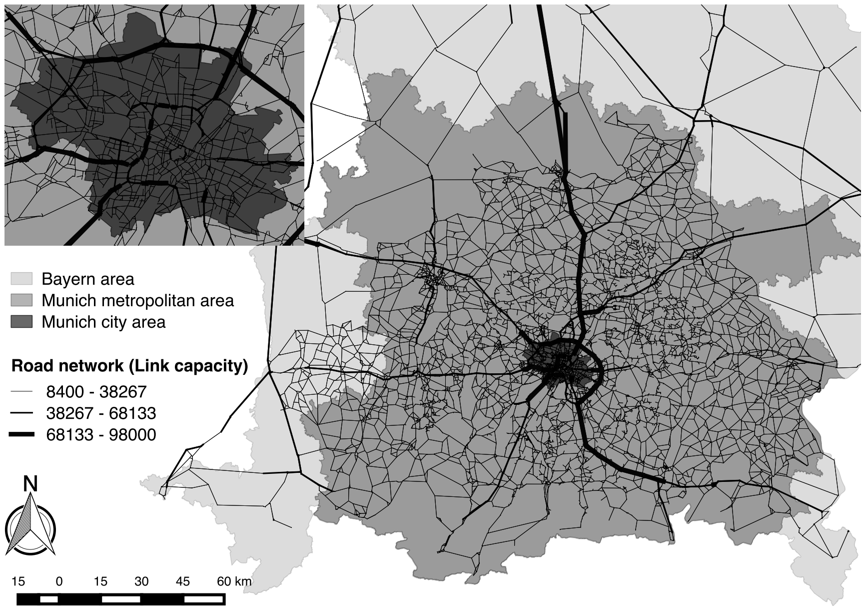


Figure 2: Munich city (inset) and metropolitan area (Agarwal , 2017).

3 Real-world scenario: Munich

In this section, the set-up for the scenario of the Munich metropolitan area (MMA) is illustrated shortly. Figure 2 shows the territorial border of Munich city and Munich metropolitan area (MMA). The initial scenario was created by Kickhöfer and Nagel (2016) and further modified by Agarwal and Kickhöfer (2016). In the present study, the latter is used. The calibrated scenario is validated against the measured traffic counts data (see Kickhöfer, 2014, for further details).

Network The network data in the form of VISUM[11] (Municipality of Munich; RSB, 2005) is converted into a MATSim network (see Figure 2).

Demand The demand is based on three different data sources, resulting in four sub-populations: urban, commuters, reverse commuters and freight. A realistic activity-based demand for each of the sub-population is created. Table 2 shows the number of individuals for each sub-population. Urban travelers are confined to Munich city area only whereas the Munich metropolitan area is populated by (rev.) commuters[12] and freight trips. For computational reasons, 1% of total population is used for the present study. Network flow and storage capacities are adjusted accordingly. In the simulation, only car mode is simulated on the network, all other modes are assumed to run emission free and without capacity constraints. There-

[11] 'Verkehr In Städten UMlegung', see www.ptv.de

[12] Reverse commuters are defined as demand that starts their trip inside Munich city and terminate their trip outside Munich city.

Table 2: User groups in the Munich metropolitan area.

User group	Data source	#Agents [m]	Travel modes
Urban	Follmer et al. (2004)	1.4	car, PT, bike, walk,ride
Commuters	Böhme and Eigenmüller (2006)	0.3	car, PT
Rev. commuters		0.2	
Freight	ITP and BVU (2007)	0.15	car

fore, in the present study, all modes other than car are depicted as *non-car* travel modes however an agent can switch mode between car and public transport (PT) as described further in re-planning strategies.

Study area The study area includes Munich city, Munich metropolitan area (MMA) and Bayern area (only former two areas are shown in Figure 2). However, the demand data comprises demand inside and from/to Munich city. Demand (and therefore emissions) in the surrounding areas that do not start or end in Munich city are not included.

Interpretation of utility parameters Following the study by Agarwal and Kickhöfer (2016), the present study also uses two different PT modes and consequently two ASCs for each PT mode. All behavioral parameters and the approximate average Values of Travel Time Savings ($VTTS$)[13] are listed in Table 3. Considering marginal utility of time as a resource, if travel time of a person is increased by Δt, he not only loses utility for traveling ($= \beta_{trav} \cdot \Delta t$) but also loses additional utility by not performing an activity ($= \beta_{dur} \cdot \Delta t$). In general, the latter is referred as an effect of the opportunity cost of time. From Table 3, the marginal utility of traveling for car and PT modes are 0 and -0.18 respectively. However, effectively, an agent will lose $-(0.0) + 0.96 = 0.96$ and $-(-0.18) + 0.96 = 1.14$ utilities every additional hour for traveling by car and PT respectively. Further, the value of travel time savings at the typical duration of an activity is given by

$$VTTS = \frac{-\beta_{trav} + \beta_{dur}}{\beta_m} .$$

Thus, the $VTTS$ for car and PT are given by $0.96/0.079 = 12.15 EUR/h$ and $1.14/0.079 = 14.43 EUR/h$ respectively.

[13] The $VTTS$ is defined as the individual willingness-to-pay for reducing the travel time by one hour. For linear utility functions, it is the ratio of the marginal utility of travel time and the marginal utility of money. The former is the sum of the dis-utility for traveling $\beta_{trav,mode(q)}$ and the negative utility of time as a resource $-\beta_{dur}$. Please note that the person-specific $VTTS$ in MATSim can vary significantly with the time pressure which an individual experiences. This is because of the non-linear utility function for performing activities, influencing the actual value of β_{dur} (see Kaddoura and Nagel, 2016, for further details).

Table 3: Behavioral parameters. † The marginal utility of money in MATSim typically is positive, since monetary costs or fares are counted negative.

Parameter	Value	Unit
Source: Agarwal and Kickhöfer (2016)		
Marginal utility of activity duration (β_{dur})	+ 0.96	$utils/h$
Marginal utility of traveling by car ($\beta_{trav,car}$)	− 0.00	$utils/h$
Marginal utility of traveling by PT ($\beta_{trav,PT}$)	− 0.18	$utils/h$
Monetary distance rate by car ($\gamma_{d,car}$)	− 0.30	EUR/km
Monetary distance rate by PT ($\gamma_{d,PT}$)	− 0.18	EUR/km
Marginal utility of money (β_m)	+ 0.079†	$utils/EUR$
Approximate average $VTTS_{car}$	+ 12.15	EUR/h
Approximate average $VTTS_{PT}$	+ 14.43	EUR/h
ASC for urban PT	− 0.75	$utils$
ASC for commuters/reverse commuters PT	− 0.3	$utils$

Re-planning strategies Two re-planning strategies are used in order to allow agents to react towards the different pricing schemes: route choice and mode choice. In every iteration, 15% agents switch route, 15% agents switch mode[14], and rest of the agents chose a plan from their existing choice set according to multinomial logit (MNL) model. After 80% of the iteration, agents only choose from their fixed choice set.

Simulation procedure Figure 3 exhibits the simulation procedure for the different scenarios under consideration. A base case simulation is run for 1000 iterations and its output is then used as input for the different policy cases:

- The base case is continued for 500 more iterations and is referred to as "Business As Usual"(BAU) case. This is the reference case for comparison.
- In order to estimate the toll levels corresponding to optimal pricing of air pollution externalities, a simulation is run using emission cost factors from the literature (see Table 1) for 500 iterations. The emission cost multiplication factor (ECMF) for this scenario is set to 1.0.
- Further five different ECMFs, namely 5.0, 10.0, 15.0, 20.0, and 25.0, are considered and one simulation is set up and for each ECMF by running it for 500 iterations.

In each of the pricing schemes, the ECMF are set to the above mentioned values to increase the highly differentiated tolls for the agents by that factor. The reaction of

[14] According to the Agarwal and Kickhöfer (2016), an urban traveler can switch mode between car and slower PT (speed 25 km/h) whereas, commuters and reverse commuters can switch mode between car and faster PT (speed 50 km/h).

the agents under various ECMF is analyzed next.

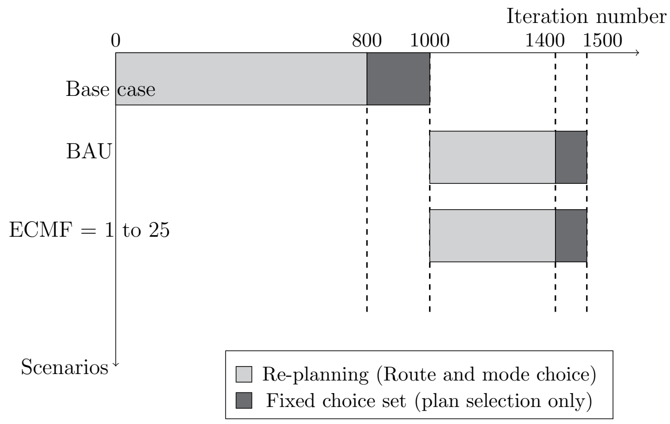


Figure 3: Iteration flow for different scenarios.

4 Results

The presentation of the results is performed from two different angles: (a) based on the geographical area, e.g. city area or metropolitan area, and (b) based on the sub-population (also called user group), namely urban, (rev.) commuters, and freight.

In order to compare the results from different policy scenarios, a 'Business As Usual' (BAU) scenario is considered in which agents are not charged for their emissions. Further, results of BAU scenarios are compared with two policy scenarios i.e. optimal pricing and backcasting. The former represents marginal social cost pricing in which emission cost multiplication factor (ECMF) in unity whereas for the latter, different values of ECMF (= 5 to 25 at an interval of 5) are used. The simulation procedure for BAU and two policy scenarios are explained in Section 3. For about the same level of emissions, agents perceive different levels of tolls for optimal pricing and backcasting. Since, these tolls are included in the decision-making process of individual (see Equation 4), agents react differently under both policy scenarios. The output of each simulation run is analyzed and results of optimal pricing as well as backcasting are compared with BAU scenario (see Sections 4.2 and 4.3) to identify the policy implications.

Table 4: Daily emission costs for the BAU scenario. The numbers indicate absolute costs (in $EUR \cdot 10^6$), and relative shares in brackets (in %). All values are scaled to the full population.

Sub-populations for the whole area				
	urban	**(rev.) commuter**	**freight**	**total**
	a	**b**	**c**	**= a+b+c**
Total emissions costs	0.20 (5.47)	0.96 (25.95)	2.55 (68.58)	3.71 (100)
Number of trips [m]	1.27 (62.66)	0.60 (29.52)	0.16 (7.82)	2.04 (100.00)
Total car distance [m km]	7.81 (11.35)	43.31 (62.95)	17.68 (25.7)	68.8 (100)
Area[15]				
	Munich city	**MMA**	**rest**	**total**
	a	**b**	**c**	**= b+c**
Total emissions costs	0.38 (10.24)	1.73 (46.63)	1.98 (53.37)	3.71 (100)
Number of links	4804 (11.45)	35317 (84.21)	6624 (15.79)	41941 (100)
Total car distance [m km]	14.04 (20.35)	45.86 (66.66)	22.94 (33.34)	68.8 (100)

4.1 The amplitude of emissions costs

Table 4 shows that the absolute daily emission costs for the BAU scenario caused by all sub-populations for the whole area amounts to 3.71 m EUR. Though, freight trips represent roughly 7.82% of all car trips, they contribute to approximately 68.58% of the emission costs because freight vehicles emits more emissions than other vehicles and have longer travel distances (mean and median trip distances are 111 and 69 km, respectively). On the other hand, the share of urban car trips is 62.66% of all car trips, but these contribute to only 5.47% of total emission costs. When looking at the emission costs inside the Munich city area, it appears that only 10.24% of the total costs are accumulated here, but urban travelers are responsible for more than half of these costs (i.e. 0.20 m EUR out of 0.38 m EUR).

The emission costs inside MMA (including the emission costs inside Munich city area) is four times higher than those in the Munich city area; the total distance traveled by car/truck inside MMA is three times more than that of the total distance traveled inside the Munich city. For conventional petrol/diesel vehicles, the traveled distances remain the crucial factor for total emission costs. Figure 4 exhibits that in the BAU scenario, almost the entire costs caused by urban travelers accumulate inside Munich city, whereas the share of emission costs from freight inside Munich city is rather small. Furthermore, one can observe that most of the emission costs caused by (rev.) commuter is emitted inside the metropolitan area, but outside of Munich city. Freight is responsible for most of the emission costs, causing the major share outside the metropolitan area.

[15] Please also note that the area outside MMA and inside total study area is defined as "rest". Since MMA already includes the values inside Munich city, the values for MMA and "rest" sum up to the total values.

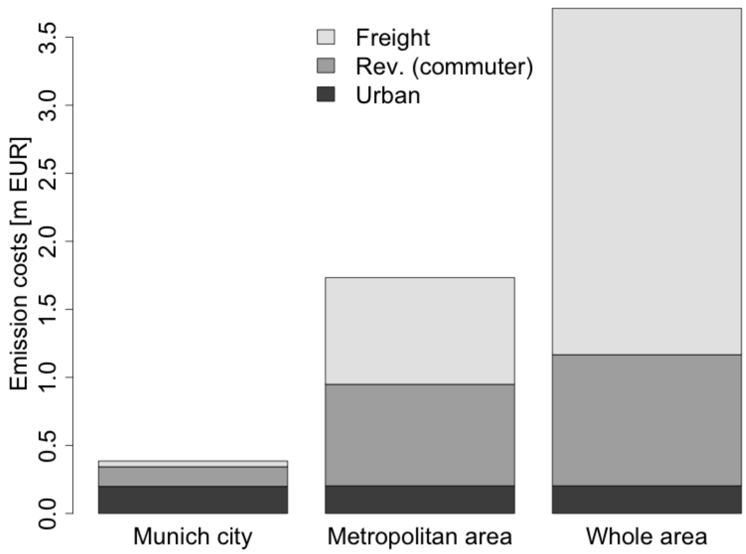


Figure 4: Contribution of sub-populations to emission costs in different regions for the BAU scenario.

4.2 Changes in monetary values of emissions

Before analyzing the changes in CO_2 emissions, the impact of the pricing schemes under investigation on total emission costs is analyzed (see Section 2.2 for the process to estimate the emissions costs). Figure 5 shows that the overall emission costs decrease with increasing ECMF. This reduction in emission costs is a combined effect of re-routing and modal shift towards environmentally friendly modes. As shown in Table 5, the modal shift is the driving force behind these savings. (Rev.) commuters are better off by shifting to PT already at low values of ECMFs, because the longer traveled distances steer their costs. In contrast, emission costs caused by urban travelers first decrease marginally (about 0.08%), then increase (about 2%) for ECMF = 5 and then decrease again. The significant decrease in the car share of (rev.) commuters (see Table 5) leads to capacity relief in the network and makes car travel more attractive again, in particular in the city and for short trips. As a consequence, the car share for urban travelers increases and ultimately results in higher emission costs at ECMF = 5. With even higher ECMFs, the tolls for urban travelers become so high that even after further relief in the capacities, urban travelers are better off by changing to PT. For freight transport, where only route choice is allowed, the decrease in emission costs is – as expected – by far smaller than for the other sub-populations. In Munich city, however, freight-related emissions costs strongly decrease compared to the other areas at higher levels of ECMF. This effect will be discussed more when looking at different pollutant types in the Section 4.3. For now, let it suffice to say that it has to do with a relief in network capacities, and the associated shift from stop and go to free flow traffic conditions and by tendency

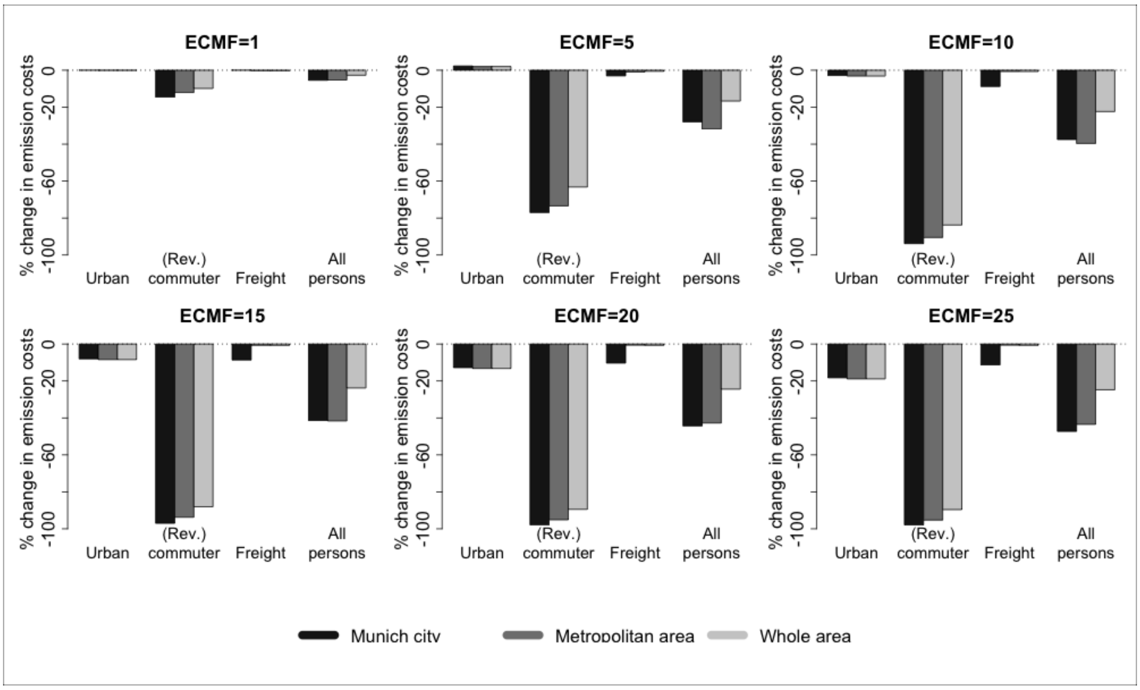


Figure 5: Relative change in monetary values of emission by sub-population and area.

Table 5: Change in car trips (in percentage points) with respect to BAU for various ECMF.

User group	**BAU**	**Emissions cost multiplication factor**					
		1	**5**	**10**	**15**	**20**	**25**
Urban	22.98	0.22	1.39	1.14	0.66	0.20	-0.41
(Rev.) commuter	65.57	-7.04	-44.96	-59.57	-62.71	-63.61	-63.67
Freight	100.00	no change					
Total	30.72	-0.79	-5.06	-7.29	-8.12	-8.63	-9.15

to shorter routes (in Munich city).

Overall, for the whole area and all sub-populations, ECMF and caused emission costs are inversely proportional to each other, i.e. an increase in the ECMF yields a decrease in emission costs. However, this effect stagnates at higher values of the ECMF (> 10). The goal of a 20% reduction of emission costs (local pollutants *and* CO_2) can be achieved for the whole area with a cost factor of 10; a cost factor of 5 is needed to achieve this target inside Munich city and the metropolitan area.

4.3 Changes in pollutant types

Following the overall interpretation from above, the effects on two types of pollutants are presented next. Section 4.3.1 exhibits the changes in CO_2 emissions for the sub-populations in different areas; Section 4.3.2 summarizes the effect of ECMFs on Non-Methane Hydrocarbons (NMHC).

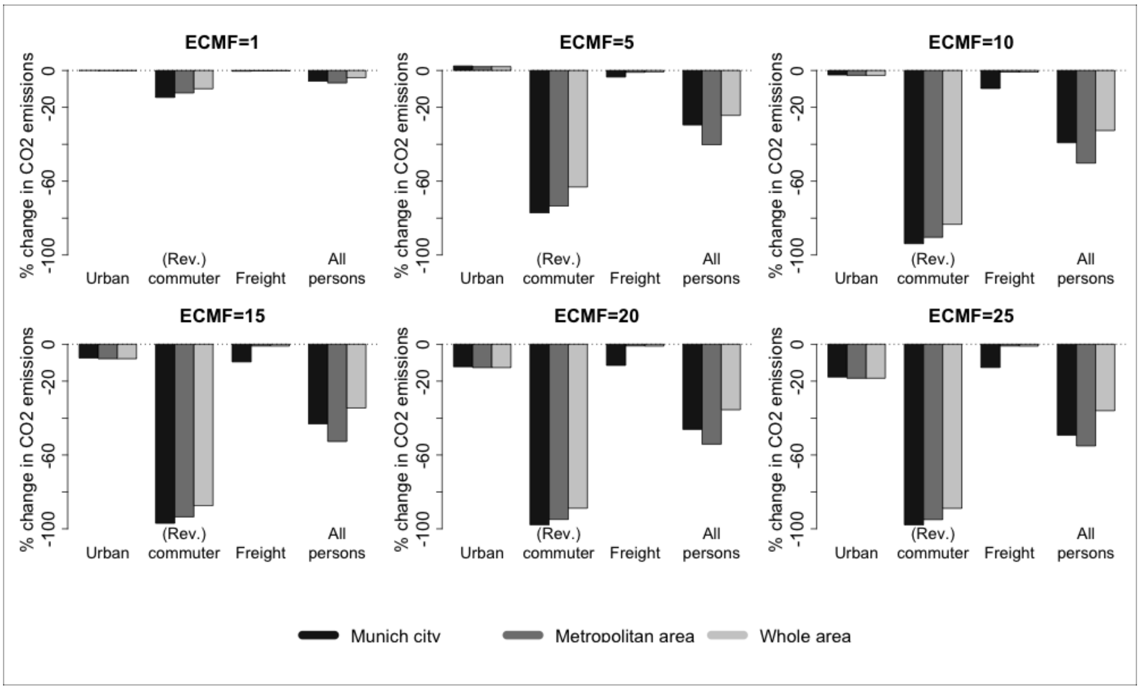


Figure 6: Effect of ECMF on CO_2 emissions by sub-population and area.

4.3.1 Changes in CO_2

Figure 6 shows the relative change in CO_2 levels for various ECMF. The overall trend is similar to the change in emission costs (see Figure 5), i.e. for (rev.) commuter, CO_2 decreases significantly with an increase in the ECMF and then becomes stationary after ECMF = 15. For freight, the decrease in CO_2 levels is very small except in city area because, freight reroutes and avoid links inside city area or shift to shorter distance routes. In contrast, for urban travelers, CO_2 level remains almost same at ECMF = 1, increases at ECMF = 5 and afterwards, decreases with an increase in the ECMF. The increase at ECMF = 5 is due to the capacity relief effect (see Section 4.2).

Interestingly, the EU emission reduction target (20% reduction in CO_2 emissions) can be achieved at ECMF = 5 (light grey bar on the right). Recall that for a 20% reduction in the total emission costs, an ECMF = 10 or higher was needed for whole area and ECMF = 5 or higher for Munich city and the metropolitan area, respectively. Thus, a toll five times higher than using the damage cost estimates results in 20% lower CO_2 levels. Consequently, the implicit costs of CO_2 with this measure amount to 350 EUR/ton (see Table 1 for the initial cost factors).

4.3.2 Changes in NMHC

The emission level of NMHC emissions mainly depends on the fuel type, engine type, age of the vehicle and vehicle speed (Haszpra and Szilágyi, 1994). NMHC emissions are higher for the cold-starts than for a warmed up vehicle (Schmitz et al., 2000;

Hoekman, 1992).

For the BAU scenario, urban travelers contribute to about 39% of total NMHC emissions because they (a) travel relatively shorter distance (average distance = 6.11 km), and (b) perform multiple trips in a day, whereas (rev.) commuters and freight only perform 2 and 1 trip(s) per day, respectively. All pollutants except NMHC show similar trends as CO_2; the changes in NMHC emissions for urban and freight user groups show an exceptional trend, which is presented next.

Figure 7a shows the effect of the different pricing schemes on NMHC levels for urban travelers and freight, aggregated for whole scenario. The following points can be observed:

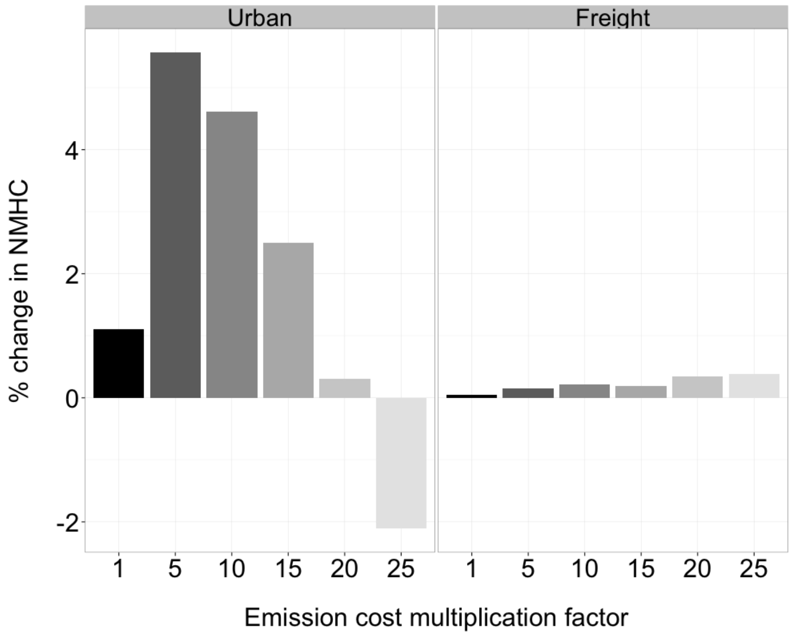
1. **Urban:** As discussed above, pricing emission increases the number of urban car trips (see Table 5) and decreases their average car distance (see Figure 7b). That is, some of the PT users with short trip distance are better off by shifting to car mode. This eventually results in higher NMHC emissions for urban travelers On the contrary, at ECMF = 25, even after the decrease in average trip distance, the NMHC costs is reduced by more than 2% due to a significant drop in car share.

2. **Freight:** The freight sub-population is different than all other sub-populations. The average trip distances decrease with increasing ECMF, but NMHC emissions increase. The average trip distance of freight trips is very high (average distance = 111 km), therefore, it is less likely that the small change in average trip distance will impact the NMHC emissions significantly. Furthermore, the freight vehicle fleet, fuel type, age of the vehicle do not vary in the scenario. Thus, the reason for the increase in NMHC results from freight trips shifting from motorways to local roads where the engine of trucks works in a different environment.

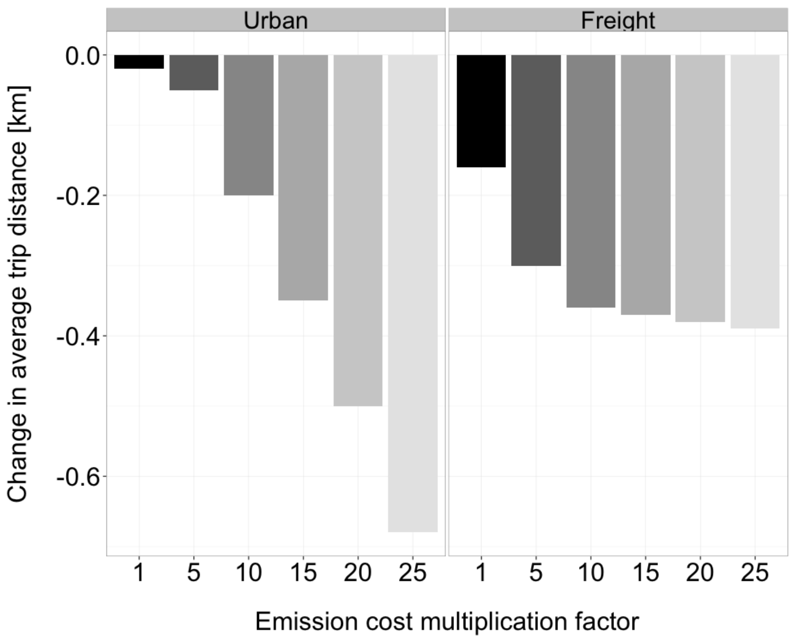
Overall, the analyses show that the CO_2 reduction target may be achieved at ECMF = 5. However, this may also lead to some adverse effects due to the changes in the local pollutants such as NMHC, which eventually helps in building of Ozone. The high amount of ground-level Ozone can be harmful to respiratory systems of people/animals and also harmful to crops however, it does not contribute to climate change.

5 Discussion

The ongoing efforts to cut global GHG emissions face various road blocks, such as the growing divergence between vehicle emissions under laboratory and real-world



(a) Relative change in NMHC levels.



(b) Absolute change in average trip distance.

Figure 7: Change in NMHC levels and average trip distance for urban and freight sub-populations with respect to BAU. Values are aggregated for scenario.

conditions, continuous economic (and thus transport) growth, or rebound effects counteracting technological improvements. Research on sustainable transportation and several real-world examples have shown that pricing schemes can help to reduce transport-related externalities such as GHG emissions. However, in order not to harm the economy, estimates for damage cost are required, which need to be in the same order of magnitude as the external effect. Since the uncertainty range for these costs is very high, the exact determination of external environmental and health costs is close to impossible. Additionally, the cost factors for local pollutants vary highly depending on the number of affected individuals or buildings eventually leading to very complex pricing schemes (see, e.g., Kickhöfer and Kern, 2015; Agarwal and Kaddoura , 2018). In such situations it can be useful to define goals on the political level, which implies setting the costs depending on the measures implemented to reach the goals. In this paper, a parametric backcasting approach is applied to a real-world case study to determine the necessary costs as multiples of the original damage cost estimates to achieve a 20% reduction in CO_2 emissions from motorized individual transport.[16] In the following, necessary assumptions and simplifications are discussed in the light of their impact on the overall results.

Base and projected year demand The urban travel demand is synthesized using detailed survey data from 12/2001 to 12/2002 (MiD 2002; Follmer et al., 2004). Because of the absence of detailed demand and vehicle fleet data from the reference year 1990, the emission reduction target for CO_2 of 20% it applied to the survey year. The following qualitative statements can be made:

a) Overall CO_2 emissions from road transport in the survey year are approximately 20% higher than 1990 levels (Eurostat, 2016). If this was also true for the scenario under consideration, then the upper bound objective would be to cut emissions approximately by 33% from the survey year. Consequently, the costs would be higher than the values estimated in this paper.

b) If the introduction of advanced vehicle and fuel technology had compensated the increasing demand for road transport in the past, then the cost estimates from this paper are required to achieve the EU emission reduction target. In other words, if advanced vehicle and fuel technology does not compensate for increasing road transport demand and rebound effects in the future, then the the costs would be higher than the values estimated in this paper.

[16] In 2030 climate and energy framework (European Union, 2018), newer target is set to cut emissions by 30% with respect to year 2005 in non-ETS (non-EU emissions trading system) sector. A similar methodology can be used identify the additional prices would require to meet this goal.

Estimated price for CO_2 The base damage cost estimate for CO_2 used in this study is 70 EUR/ton (see Table 1). This value is already rather high compared to most estimates in other studies (see, e.g. Maibach et al., 2008, pp. 262-263; Tol, 2005). The proposed backcasting approach finds that the base estimate for CO_2 needs to be increased by a factor of 5 (i.e. 350 EUR/ton), which is even higher than very high estimates from the literature with approximately 280 EUR/ton (see, e.g., Krewitt and Schlomann, 2006; Maibach et al., 2008). The costs required to reduce the CO_2 emissions by 20% in this scenario are consequently rather high, ignoring the fact that a similar emission reduction might be achieved more economically in other sectors.

Simulation of non-car users In this study, cars and trucks are simulated using a network loading algorithm. The remaining modes are simulated using a custom teleportation speed and beeline distance (see Chapters 7 and 9 in Agarwal , 2017, for details). This implies that these non-network modes are assumed to run emission and congestion free, which holds as long as they are in reality operated on a separate infrastructure and run on electric power from renewable energy. If that is not the case, total emissions and, hence, the necessary ECMFs obtained in this study to achieve the reduction goal are likely to be underestimated. Furthermore, it is assumed that the PT system is able to handle additional demand resulting from mode switchers as a reaction to the tolls. In reality, PT capacity is restricted, and the respective external costs should be included in future research (see, e.g., Kaddoura et al., 2015, for a possible way to include PT capacity constraints in the MATSim framework). Finally, travelers are in this study only allowed to switch between car and PT. In reality, other options are available, which are captured by the emission and congestion free PT. In that sense, PT can be interpreted as a placeholder for all non-car modes, and differentiating them in the simulation is therefore unlikely to change the results structurally. In future research, however, it will be important to model PT with capacity constraints and emissions. The newly developed MATSim scenario for Santiago de Chile (Kickhöfer et al., 2016) offers this possibility.

Sensitivities and elasticities We see, from Figure 5 and Table 5, that reaching a 20% goal (be it of all emissions or CO_2 only) hinges on the commuters switching to the emissions free ("fast" PT) mode. For a commuting distance of, say, $d = 50\ km$, the linearized scoring contributions are

$$
\begin{aligned}
S_{car} &= ASC_{car} + (\beta_{car} - \beta_{dur}) \cdot t_{car} + \beta_m \cdot \gamma_{d,car} \cdot d \\
&= 0 - 0.96 \tfrac{1}{h} \cdot 1\,h - 0.079 \tfrac{1}{EUR} \cdot 0.3 \tfrac{EUR}{km} \cdot 50\,km \\
&= 0 - 0.96 \tfrac{1}{h} \cdot 1\,h - 0.079 \tfrac{1}{EUR} \cdot 15 EUR \\
&= - 0.96 - 1.185 \\
&= -2.145 \\
S_{PT} &= ASC_{fast.PT} + (\beta_{fast.PT} - \beta_{dur}) \cdot t_{PT} + \beta_m \cdot \gamma_{d,PT} \cdot d \\
&= -0.3 + (-0.18 - 0.96) \tfrac{1}{h} \cdot 1\,h - 0.079 \tfrac{1}{EUR} \cdot 0.18 \tfrac{EUR}{km} \cdot 50\,km \\
&= -0.3 - 1.14 \tfrac{1}{h} \cdot 1\,h - 0.079 \tfrac{1}{EUR} \cdot 9\ EUR \\
&= -0.3 - 1.14 - 0.711 \\
&= -2.151
\end{aligned}
$$

where it is assumed that the trip, because of car congestion, takes 1 hour both by car and by PT; clearly, the car travel time would rather be emergent by the model.

The same calculation in money space is obtained by dividing everything by $\beta_m = 0.079/EUR$, resulting in

$$
\begin{aligned}
M_{car} &= 0 - 12.15 \tfrac{EUR}{h} \cdot 1\,h - 0.3 \tfrac{EUR}{km} \cdot 50\,km \\
&= - 12.15\ EUR - 15\ EUR \\
&= -27.15\ EUR \\
M_{PT} &= \tfrac{-0.3}{0.079/EUR} - 14.43 \tfrac{EUR}{h} \cdot 1\,h - 0.18 \tfrac{EUR}{km} \cdot 50\,km \\
&\approx -3.8\ EUR - 14.43\ EUR - 9\ EUR \\
&= -27.23 EUR\ .
\end{aligned}
$$

All these terms are plausible for Munich standards.

Clearly, one could now assume a logit choice model based on these and then compute elasticities. This is, however, not straightforward, since changes in mode share lead to changes in congestion, thus affecting t_{car}. Kickhöfer et al. (2013) perform a corresponding simulation-based study with a similar model and obtain elasticities in the same range as those found in the literature.

So in the end we find little reason to waiver on these parameters: the out-of-pocket costs are plausible, the $VTTS$ are plausible, and the ASC was calibrated such that mode choice was plausible, and consistent with congestion.

Agarwal and Kickhöfer (2016) (Table 8) now state that the average emissions toll for ECMF=1 would be 0.0224 EUR/km, or 1.12 EUR for the 50 km considered here. Compared to the base disutility of the car trip of 27.15 EUR or even just to the already incurring monetary costs of 15 EUR, this is a relatively small amount, and it is therefore intuitively plausible that the mode choice reaction is not sufficiently strong to reach the emissions reduction goal.

Sensitivity to the Value of Travel Time Savings Some cities around the globe have installed relatively simple mobility pricing schemes, but they base their toll calculations at best on estimates of the true marginal costs. Consequently, little is empirically known about the reactions of users towards high resolution pricing schemes as simulated in this paper. The behavioral model in the simulation relies on estimates of the Values of Travel Time Savings ($VTTS$). Therefore, a sensitivity analysis is performed by halving and doubling the $VTTS$ from Table 3 in two additional simulation experiments, i.e. $VTTS_{test} = x \cdot VTTS_{base}$, for $x = 0.5$ and $x = 2.0$.[17] As a result, Figure 8 shows the share of car trips for urban travelers and (rev.) commuters. For (rev.) commuters, it can be observed that the car share substantially increases with the $VTTS$ for all ECMFs. The main driving force behind this are the long distances (and therefore high emission costs) for (rev.) commuters, which are perceived less negatively with increasing $VTTS$. As discussed previously in Section 4.2, the *de*crease in car mobility of (rev.) commuters leads to capacity relief, which *in*creases car mobility of urban travelers in terms of trip numbers (not kilometers traveled). This effect can be observed even more prominently if the $VTTS$ is halved, but only for BAU and ECMF = 1. For higher ECMF, the perception of toll costs dominates this capacity relief effect, and car shares of urban travelers are lower than with $VTTS_{base}$. In contrast, if the $VTTS$ is doubled, network capacity utilization of (rev.) commuters increases, and the share of urban car trips decreases. Overall, it can be summarized that an increase in the $VTTS$ will increase the overall car share and, thus, eventually increase the additional factor required to reach the EU 2020 CO_2 reduction targets.

Effect of combined pricing schemes on emission costs A combined pricing scheme for emission and congestion is proposed by Agarwal and Kickhöfer (2015) and a positive correlation between these two externalities is found. Further, Agarwal and Kickhöfer (2016) identify the amplitude of the correlation between congestion and emission externalities. However, these combined pricing schemes are able to reduce the emissions costs only by 2.5%, and 7.2% respectively under different initial assumptions which is still far-away from the 20% reduction target.

[17] In these experiments, the $VTTS$ is halved and doubled by doubling and halving the marginal utility of money, respectively.

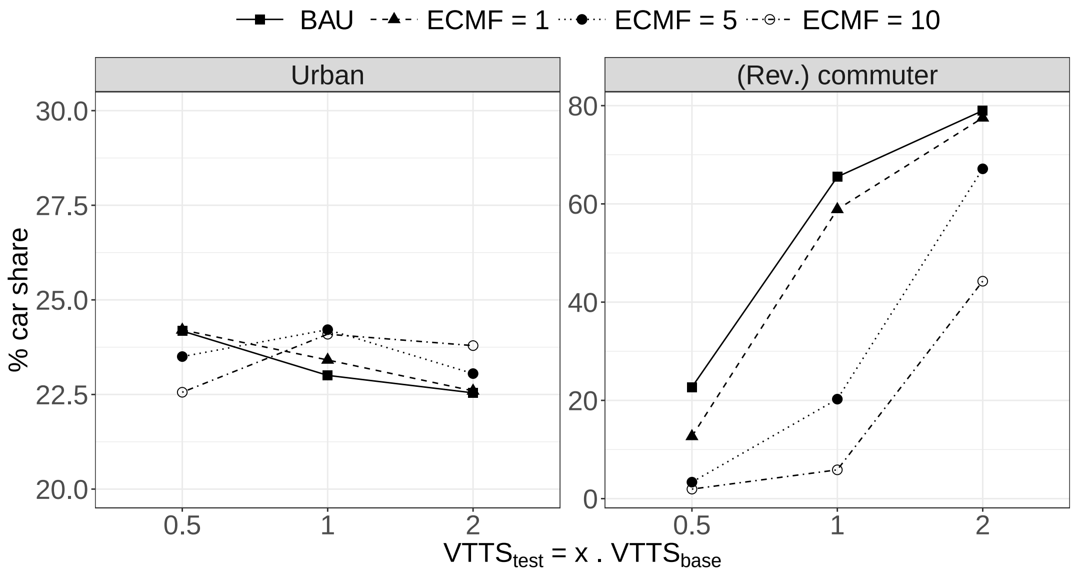


Figure 8: Share of car trips for different emission cost multiplication factors (ECMF) and different test values of $VTTS$.

Policy implications The main policy implication, clearly, is that overall magnitudes matter. According to Figure 4, most of the overall emissions costs of 3.7 m EUR ("whole area") are generated by freight, followed by (rev.) commuters, while the contribution of the urban travelers is small. Freight can only react by route choice, which in the end does not provide enough flexibility to significantly contribute to reduced emissions. Other reactions of freight, e.g. changed mode choice, are possible in reality, but quite difficult to achieve; work by Schröder et al. (2012); Nagel et al. (since 2017) will improve our modeling capabilities in this direction but is not yet operational. In consequence, nearly all of the 20% reduction, i.e. the equivalent of 0.74 m EUR, needs to be achieved by the (rev.) commuters, implying that their emission equivalents need to go from 0.9 m EUR down to 0.16 m EUR, a drastic reduction which (as the model points out) can only be achieved by a drastic toll. In other words, reaching the 20% reduction target in the transport sector seems difficult to achieve without significant reduction contributions of the freight sector.

Implementation issues The model calculates each vehicle's emissions at the end of each link, based on speed, road characteristics, engine type, engine temperature, etc., based on the HBEFA database (see Section 2.2). This computation could, in principle, be mirrored inside each vehicle, or in a central toll computation center. Note that the approach discussed in this paper targets *all* pollutants, and not just CO_2; when only targeting CO_2, it is well known that one could as well add the corresponding charge to the fuel price, e.g. 0.16 EUR/l for optimal pricing (ECMF=1) and 0.81 EUR/l for ECMF = 5.[18] However, in our view the main contribution of work such as ours at this point is to clarify the structure of the possible contributions of the sub-systems, as discussed above under "policy implications" paragraph. Clearly, once we have reached better agreement on the overall policy mix, one can again use a model such as ours to investigate possible implementation details.

6 Conclusion and outlook

This paper determined the price gap between toll levels derived from optimal emission pricing and toll levels implicitly resulting from the EU 2020 CO_2 reduction target. First, an existing optimal emission pricing approach was applied to a real-world scenario and changes in emissions and cost levels were evaluated. Second, in order to obtain the necessary toll levels required to achieve the EU 2020 CO_2 reduction target, different emission cost multiplication factors (ECMF) were used to modify the initial toll levels. The results of these scenarios were compared to the base scenario.

It was shown that ECMF = 10 is required to reduce total emission costs by 20%, whereas ECMF = 5 is enough to obtain a 20% reduction in CO_2 levels. That is, damage costs estimates from the literature have to be multiplied by a factor of 5 to achieve the EU 2020 CO_2 reduction target. Hence, this paper estimates the cost of CO_2 to 350 EUR/ton, which is significantly higher than available estimates from the literature where the damage cost approach is typically used.

The highest contribution to the emission reduction came from (rev.) commuters and their modal shift from car to PT mode. Urban travelers, however, shifted especially for short (and therefore cheap) trips to car because travel times were reduced due to this relief in road capacities. Only at very high toll levels, the car share of urban travelers decreased. For freight traffic, significant improvements in the emission levels were observed in the city area above ECMF = 5. Furthermore, the investigation of emission levels indicated that because of the increase in the number of short urban car trips, Non-Methane Hydrocarbon (NMHC) levels by tendency increased. Similarly, for freight, an increase in NMHC was observed because of route shifts from motorways to local and distributor roads. NMHC can contribute to increased Ozone levels and high amount of Ozone near ground-level is harmful for people, animal and crops.

Overall, this paper provided valuable insights about differences in price levels, potential different outcomes for the various types of pollutants and groups of trav-

[18] According to The Code of Federal Regulations (40 CFR 600.113), carbon content in diesel is 2778 $g/gallon$. Assuming, 99% of carbon is oxidized, CO_2 emissions from diesel $= 2778 \times 0.99 \times \frac{44}{12}$ $g/gallon = 8.8$ $kg/gallon = 2.32$ kg/l. From Table 1, the cost of $CO_2 = 70$ $EUR/ton = 0.07$ EUR/kg. Thus, cost of CO_2 emissions $= 2.32$ $kg/l \times 0.07$ $EUR/kg = 0.1624$ EUR/l

elers Pricing schemes for emissions might not necessarily result in a reduction of all pollutants or of the emission levels of all users. It shows how agent-based simulations can be used for quantifying the results and for decision support in such possibly counter-intuitive situations. In future research, pricing other externalities of transport (e.g. congestion, noise, accidents) should be included. Additionally, the analysis is planned to be carried out for a greater region (e.g. Germany, EU) in order to test the variability of results.

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References

2008/101/EC. Directive 2008/101/EC of the European Parliament and of the Council. Official Journal of the European Union, 2008.

A. Agarwal. *Mitigating negative transport externalities in industrialized and industrializing countries*. PhD thesis, TU Berlin, Berlin, 2017. doi:10.14279/depositonce-5825.

A. Agarwal and I. Kaddoura. On-road air pollution exposure to cyclists in an agent-based simulation framework. In *NECTAR Cluster 7 Workshop: Social and Health Issues in Transportation* 2018.

A. Agarwal and B. Kickhöfer. Agent-based simultaneous optimization of congestion and air pollution: A real-world case study. *Procedia Computer Science*, 52(C):914–919, 2015. ISSN 1877-0509. doi:10.1016/j.procs.2015.05.165.

A. Agarwal and B. Kickhöfer. The correlation of externalities in marginal cost pricing: lessons learned from a real-world case study. *Transportation*, 45(3):849–873, 2016. doi:10.1007/s11116-016-9753-z.

A. Agarwal, M. Zilske, K. Rao, and K. Nagel. An elegant and computationally efficient approach for heterogeneous traffic modelling using agent based simulation. *Procedia Computer Science*, 52(C):962–967, 2015. ISSN 1877-0509. doi:10.1016/j.procs.2015.05.173.

A. Agarwal, G. Lämmel, and K. Nagel. Incorporating within link dynamics in an agent-based computationally faster and scalable queue model. *Transportmetrica A: Transport Science*, 2017. doi:10.1080/23249935.2017.1364802.

D. Banister and R. Hickman. Techno-optimism: progress towards CO2 reduction targets in transport: a UK and London perspective. *International Journal of Sustainable Development*, 12(1): 24–47, 2009. doi:10.1504/IJSD.2009.027527.

P. Barla, B. Lamonde, L. F. Miranda-Moreno, and N. Boucher. Traveled distance, stock and fuel efficiency of private vehicles in Canada: price elasticities and rebound effect. *Transportation*, 36 (4):389–402, 2009. doi:10.1007/s11116-009-9211-2.

S. Böhme and L. Eigenmüller. Pendlerbericht Bayern. Technical report, IAB, 2006.

M. Börjesson and I. Kristoffersson. The Gothenburg congestion charge. effects, design and politics. *Transportation Research Part A: Policy and Practice*, 75:134–146, 2015. doi:10.1016/j.tra.2015.03.011.

R. Buehler and J. Pucher. Sustainable transport in Freiburg: lessons from Germany's environmental capital. *International Journal of Sustainable Transportation*, 5(1):43–70, 2011. doi:10.1080/15568311003650531.

H. Cai and S. Xie. Traffic-related air pollution modeling during the 2008 Beijing Olympic games: the effects of an odd-even day traffic restriction scheme. *Science of The Total Environment*, 409 (10):1935–1948, 2011. doi:10.1016/j.scitotenv.2011.01.025.

M. S. Divjak. Strategic land use planning for low carbon cities in Ljubljana urban region. In *45th ISOCARP Congress 2009*, 2009.

T. E. Downing, D. Anthoff, R. Butterfield, M. Ceronsky, M. Grubb, J. Guo, C. Hepburn, C. Hope, A. Hunt, A. Li, A. Markandya, S. Moss, A. Nyong, R. Tol, and P. Watkiss. Social cost of carbon: a closer look at uncertainty. Final project report, Department for Environmental, Food and Rural Affairs, 2005.

EEA. Climate for a transport change. Technical Report 1/2008, European Environment Agency, 2008.

EEA. Focusing on environmental pressures from long–distance transport – term 2014 : transport indicators tracking progress towards environmental targets in Europe. EEA Report 7/2014, European Environment Agency, 2014.

EEA. New cars' CO2 emissions well below Europe's 2015 target. Technical report, European Environment Agency, 2015.

J. Eliasson, L. Hultkrantz, L. Nerhagen, and L. S. Rosqvist. The Stockholm congestion – charging trial 2006: Overview of effects. *Transportation Research Part A: Policy and Practice*, 43:240–250, 2009. doi:10.1016/j.tra.2008.09.007.

C. M. Elmberg. The gothenburg traffic restraint scheme. *Transportation*, 1(1):1–27, 1972. ISSN 0049–4488. doi:10.1007/BF00167506.

G. Emberger. Low carbon transport strategy in Europe - a critical review. *International Journal of Sustainable Transportation*, 2015. doi:10.1080/15568318.2015.1106246.

European Commission. Roadmap to a Single European Transport Area - Towards a competitive and resource efficient transport system. White Paper, 2011. URL http://ec.europa.eu/transport/themes/strategies/doc/2011_white_paper/white-paper-illustrated-brochure_en.pdf.

European Union. EU 2020 climate and energy package. Accessed 16.11.2017. URL https://ec.europa.eu/clima/policies/strategies/2020_en.

European Union. 2030 climate and energy framework. Accessed 19.02.2018. URL https://ec.europa.eu/clima/policies/strategies/2030_en.

Eurostat. Eurostat: Your key to European statistics, 2016. Online data code:*env_air_gge*. URL http://ec.europa.eu/eurostat/data/database.

R. Ewing, K. Bartholomew, S. Winkelman, J. Walters and D. Chen. Growing cooler: the evidence on urban development and climate change. *Urban Land Institute*, 2007.

FCCC/CP/2015/L.9/Rev.1. Adoption of the Paris agreement. Framework Convention on Climate Change, United Nations, 2016.

P. Fernandes, J. M. Bandeira, T. Fontes, S. R. Pereira, B. J. Schroeder, N. M. Rouphail, and M. C. Coelho. Traffic restriction policies in an urban avenue: a methodological overview for a trade-off analysis of traffic and emission impacts using microsimulation. *International Journal of Sustainable Transportation*, 2014. doi:10.1080/15568318.2014.885622.

R. Follmer, U. Kunert, J. Kloas, and H. Kuhfeld. Mobilität in Deutschland – Ergebnisbericht. Technical report, infas/DIW, Bonn, 2004. URL www.kontiv2002.de.

K. Geurs and B. van Wee. Backcasting as a tool to develop a sustainable transport scenario assuming emission reductions of 80-90%. *Innovation: The European Journal of Social Science Research*, 13(1):47–62, 2000. doi:10.1080/135116100111658.

K. Geurs and B. van Wee. Backcasting as a tool for sustainable transport policy making: the environmentally sustainable transport study in the Netherlands. *European Journal of Transport Infrastructure Research*, 4(1):47–69, 2004.

L. Haszpra and I. Szilágyi. Non-Methane Hydrocarbon composition of car exhaust in Hungary. *Atmospheric Environment*, 28(16):1609–2614, 1994. doi:10.1016/1352-2310(94)90434-0.

R. Hickman, O. Ashiru, and D. Banister. Achieving carbon-efficient transportation : backcasting from London. *Transportation Research Record: Journal of the Transportation Research Board*, 2139:172–182, 2009. doi:10.3141/2139-20.

S. K. Hoekman. Speciated measurements and calculated reactivities of vehicle exhaust emissions from conventional and reformulated gasolines. *Environmental Science and Technology*, 26(6): 1206–1216, 1992. doi:10.1021/es50002a610.

A. Horni, K. Nagel, and K. W. Axhausen. Introducing MATSim. In A. Horni, K. Nagel, and K. W. Axhausen, editors, *The Multi-Agent Transport Simulation MATSim*, chapter 1. Ubiquity, London, 2016a. doi:10.5334/baw. URL http://matsim.org/the-book.

A. Horni, K. Nagel, and K. W. Axhausen. *The Multi-Agent Transport Simulation MATSim*. Ubiquity, London, 2016b. doi:10.5334/baw. URL http://matsim.org/the-book.

A. Horni, K. Nagel, and K. W. Axhausen. Qsim. In A. Horni, K. Nagel, and K. W. Axhausen, editors, *The Multi-Agent Transport Simulation MATSim*, chapter 11. Ubiquity, London, 2016c. doi:10.5334/baw. URL http://matsim.org/the-book.

F. Hülsmann, R. Gerike, B. Kickhöfer, K. Nagel, and R. Luz. Towards a multi-agent based modeling approach for air pollutants in urban regions. In *Conference on "Luftqualität an Straßen"*, pages 144–166. Bundesanstalt für Straßenwesen, FGSV Verlag GmbH, 2011. ISBN 978-3-941790-77-3. Also VSP WP 10-15, see http://www.vsp.tu-berlin.de/publications.

IPCC. *Climate change 2014: mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014. URL https://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_full.pdf.

ITP and BVU. Prognose der deutschlandweiten Verkehrsverflechtungen 2025. Technical report, Intraplan Consult GmbH, Beratergruppe Verkehr+Umwelt GmbH, 2007. URL http://daten.clearingstelle-verkehr.de/220/.

IWW, IFEU, KuP, PÖU, and PTV. Entwicklung eines Verfahrens zur Aufstellung umweltorientierter Fernverkehrskonzepte als Beitrag zur Bundesverkehrswegeplanung. Schlussbericht für Forschungsprojekt FE Nr. 10506001(alt) / 295 54 001 (neu), Institut für Wirtschaftspolitik und Wirtschaftsforschung, Universität Karlsruhe; Institut für Energie- und Umweltforschung GmbH; Kessel und Partner; Planungsgruppe Ökologie + Umwelt; PTVConsult GmbH, 1998. Im Auftrag des Umweltbundesamtes.

I. Kaddoura and K. Nagel. Agent-based congestion pricing and transport routing with heterogeneous values of travel time savings. *Procedia Computer Science*, 83:908–913, 2016. doi:10.1016/j.procs.2016.04.184.

I. Kaddoura, B. Kickhöfer, A. Neumann, and A. Tirachini. Optimal public transport pricing: Towards an agent-based marginal social cost approach. *Journal of Transport Economics and Policy*, 49(2):200–218, 2015. Also VSP WP 13-09, see http://www.vsp.tu-berlin.de/publications. Awarded as the Best PhD Student Paper at hEART 2013.

I. Kaddoura, A. Agarwal and B. Kickhöfer. Simulation-based optimization of congestion, noise and air pollution costs: the impact of transport users' choice dimensions. In *ITEA Annual Conference and School on Transportation Economics*, 2017. Also VSP WP 17-19, see http://www.vsp.tu-berlin.de/publications.

B. Kickhöfer. *Economic Policy Appraisal and Heterogeneous Users*. PhD thesis, TU Berlin, Berlin, 2014.

B. Kickhöfer and J. Kern. Pricing local emission exposure of road traffic: An agent-based approach. *Transportation Research Part D: Transport and Environment*, 37(1):14–28, 2015. ISSN 1361-9209. doi:10.1016/j.trd.2015.04.019.

B. Kickhöfer and K. Nagel. Towards high-resolution first-best air pollution tolls. *Networks and Spatial Economics*, 16(1):175–198, 2016. doi:10.1007/s11067-013-9204-8.

B. Kickhöfer, D. Hosse, K. Turner and A. Tirachini. Creating an open MATSim scenario from open data: The case of Santiago de Chile. VSP Working Paper, 16-02, 2016. See VSP WP 16-02, see http://www.vsp.tu-berlin.de/publications.

B. Kickhöfer, F. Hülsmann, R. Gerike, and K. Nagel. Rising car user costs: comparing aggregated and geo-spatial impacts on travel demand and air pollutant emissions. In T. Vanoutrive and A. Verhetsel, editors, *Smart Transport Networks: Decision Making, Sustainability and Market structure*, NECTAR Series on Transportation and Communications Networks Research, pages 180–207. Edward Elgar Publishing Ltd, 2013. ISBN 978-1-78254-832-4. doi:10.4337/9781782548331.00014.

W. Krewitt and B. Schlomann. Externe kosten der stromerzeugung aus erneuerbaren energien im vergleich zur stromerzeugung aus fossilen energieträgern. Technical report, Zentrums für Sonnenenergie- und Wasserstoff-Forschung Baden-Württemberg (ZSW), 2006.

H. Link, C. Nash, A. Ricci, and J. Shires. A generalised approach for measuring the marginal social costs of road transport in Europe. *International Journal of Sustainable Transportation*, 2014. doi:10.1080/15568318.2013.861044.

J. Liu and G. Santos. Decarbonizing the road transport sector: break-even point and consequent potential consumers' behavior for the U.S. case. *International Journal of Sustainable Transportation*, 9(3):159–175, 2015. doi:10.1080/15568318.2012.749962.

M. Maibach, D. Schreyer, D. Sutter, H. van Essen, B. Boon, R. Smokers, A. Schroten, C. Doll, B. Pawlowska, and M. Bak. Handbook on estimation of external costs in the transport sector. Technical report, CE Delft, 2008. URL http://ec.europa.eu/transport/sites/transport/files/themes/sustainable/doc/2008_costs_handbook.pdf. Internalisation Measures and Policies for All external Cost of Transport (IMPACT).

A. D. May. Urban transport and sustainability: the key challenges. *International Journal of Sustainable Transportation*, 7(3):170–185, 2013. doi:10.1080/15568318.2013.710136.

P. Mock, U. Tietge, V. Franco, J. German, A. Bandivadekar, N. Ligterink, U. Lambrecht, J. Kühlwein, and I. Riemersma. From laboratory to road : A 2014 update of official and "real–world" fuel consumption and CO_2 values for passenger cars in Europe. White paper, International Council on Clean Transportation, 2014.

K. Nagel, G. Flötteröd. Agent-based traffic assignment: Going from trips to behavioural travelers. In R.M. Pendyala, C.R. Bhat, editors, *Travel Behaviour Research in an Evolving World – Selected papers from the 12th international conference on travel behaviour research*, International Association for Travel Behaviour Research, 2012. pp 261-294.

K. Nagel, B. Kickhöfer, A. Horni, and D. Charypar. A closer look at scoring. In A. Horni, K. Nagel, and K. W. Axhausen, editors, *The Multi-Agent Transport Simulation MATSim*, chapter 3. Ubiquity, London, 2016. doi:10.5334/baw. URL http://matsim.org/the-book.

K. Nagel, G. Liedtke and J. Joubert. Carrier Agents and Interactions withTraffic Flows. Project, since 2017.

K. Nakamura and Y. Hayashi. Strategies and instruments for low-carbon urban transport: An international review on trends and effects. *Transport Policy*, 29:264–274, 2013. doi:10.1016/j.tranpol.2012.07.003.

I. Parry and K. Small. Does Britain or the United States have the right gasoline tax? *The American Economic Review*, 95(4):1276–1289, 2005. doi:10.1257/0002828054825510.

I. W. Parry, D. Evans, and W. E. Oates. Are energy efficiency standards justified? *Journal of Environmental Economics and Management*, 67(2):104–125, 2014. doi:10.1016/j.jeem.2013.11.003.

J. Romm. The car and fuel of the future. *Energy Policy*, 34(17):2609–2614, 2006. doi:10.1016/j.enpol.2005.06.025.

L. Rotaris, R. Danielis, E. Marcucci, and J. Massiani. The urban road pricing scheme to curb pollution in Milan, Italy: Description, impacts and preliminary cost–benefit analysis assessment. *Transportation Research Part A: Policy and Practice*, 44(5):359–375, 2010. doi:10.1016/j.tra.2010.03.008.

RSB. Municipality of Munich: Referat für Stadtplanung und Bauordnung, 2005.

T. Schmitz, D. Hassel, and F.-J. Weber. Determination of VOC-components in the exhaust of gasoline and diesel passenger cars. *Atmospheric Environment*, 34(27):4639–4647, 2000. ISSN 1352-2310. doi:10.1016/S1352-2310(00)00303-4.

J. Schoemaker, A. Scholtz, and R. Enei. Towards low carbon transport in Europe. Technical report, Transport Research and Innovation Portal (TRIP), 2012.

S. Schröder, M. Zilske, G. Liedtke and K. Nagel. Towards a Multi-Agent Logistics and Commercial Transport Model: The Transport Service Provider's View. *Procedia Social and Behavioral Sciences*, 39:649–663, 2012. doi:10.1016/j.sbspro.2012.03.137.

B. A. Thomas and I. L. Azevedo. Estimating direct and indirect rebound effects for U.S. households with input–output analysis Part 1: theoretical framework. *Ecological Economics*, 86:199–210, 2013. doi:10.1016/j.ecolecon.2012.12.003.

R. S. J. Tol. The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. *Energy Policy*, 33(16):2064–3074, 2005. doi:10.1016/j.enpol.2004.04.002.

R. Turvey. On divergences between social and private cost. *Economica*, 30(119):309–313, 1963. doi:10.2307/2601550.

E. Verhoef. Marginal cost based pricing in transport. Key implementation issues from the economic perspective, 2001. Paper presented at Seminar One of IMPRINT-EUROPE.

A. A. Walters. The theory and measurement of private and social costs of highway congestion. *Econometrica*, 29(4):676–699, 1961. doi:10.2307/1911814.

P. Watkiss, D. Anthoff, T. Downing, C. Hepburn, C. Hope, A. Hunt, and R. Tol. The social cost of carbon (SCC) review: methodological approaches for using SCC estimates in policy assessment. Final report, Department for Environment, Food and Rural Affairs (Defra), London, 2005.

Y. Zhou, Y. Wu, L. Yang, L. Fu, K. He, S. Wang, J. Hao, J. Chen, and C. Li. The impact of transportation control measures on emission reductions during the 2008 Olympic games in Beijing, China. *Atmospheric Environment*, 44(3):285–293, 2010. doi:10.1016/j.atmosenv.2009.10.040.